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Information Adoption Patterns and Online Knowledge Payment Behavior: The Moderating Role of Product Type

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Abstract: The development of online knowledge payment platforms in recent years has increased their respective market value by nurturing content resources and improving content ecology. Yet, the underlying factors of knowledge seekers' payment behaviors and their information adoption mechanisms are poorly understood. Based on the information adoption model, this study develops a research model to examine the relationship between information adoption patterns and knowledge seekers' payment behavior, and explore the moderating effect of product type on this relationship. To test the research model and hypotheses, we used a multi-analytic approach combining text and regression analysis on a sample of 4366 social Q&A data collected from Quora+ between August 2021 and August 2022. We further classified the product types into utilitarian and hedonic, and compared the differences in influence paths between product types. The results show that the completeness, vividness, and relevance of the product description have a significant positive impact on knowledge payment behavior. The reputation, experience, and integrity of the knowledge provider have a positive impact on knowledge payment behavior. Compared to utilitarian knowledge products, the payment behavior for hedonic products is more related to the reputation and experience of the knowledge provider. This study provides insights into the factors that influence online knowledge payment behavior and practical guidance for the development of online knowledge payment services and platforms.

Keywords: online knowledge payment behavior; information adoption model; information quality; knowledge provider credibility; product type

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1. Introduction

With the global shift toward knowledge economy and the growing demand for knowledge products and services, knowledge supply and demand have evolved from a free to a paid knowledge model, where knowledge providers create standardized and structured paid knowledge products in a systematic process. These knowledge products are then made available to knowledge seekers through subscription mechanisms of knowledge payment platforms. Notable industry leaders include platforms such as Quora, Yahoo! Answers, and Stack Overflow in the United States; Knowledge-iN in Korea; and Baidu Knows, Himalaya FM, and Zhihu in China. In recent years, the knowledge payment market has developed and grown rapidly due to the large number of people seeking to acquire and improve knowledge and the influence of marketing anxiety [1,2]. In China, for example, the knowledge payment industry was valued at around 4.9 billion yuan in 2017 [3]. The transaction volume of the knowledge payment services market in China is growing at a rate of 205 percent [4], indicating the huge growth potential of knowledge payment services investment in the Chinese market. The number of knowledge payment service users increased from 48 million in 2015 to 292 million in 2018, with an average growth rate of 82.5%. In parallel, the market size increased from 1.59 billion yuan in 2015 to 16.58 billion yuan in 2018, with an average growth rate of 118.5%. During the prevention and control period of the COVID-19 epidemic in the spring of 2020, the traditional offline economy has suffered greatly, while the knowledge-based payment market has opened a new development opportunity. According to recent surveys [5], nearly 90% of users purchased knowledge products in 2020, with 63.1% of users purchasing knowledge products during the epidemic period, primarily focused on job-related skills and interpersonal skills training.

Despite the growing prosperity of the knowledge monetization industry, the praxis shows that the success of knowledge payment markets and platforms remains questionable. Knowledge providers do not generate sufficient revenue or profits from marketing their expertise on online knowledge payment platforms. Moreover, it remains a challenge for knowledge providers to create an environment for paid knowledge exchange with knowledge seekers because knowledge products are intangible, inseparable, and heterogeneous [2]. Therefore, knowledge seekers have to bear high risk due to their limited prior knowledge before purchase [6], which in turn affects their experience and satisfaction [7]. According to a recent study by Yu, Chen [8], 50.6% of Internet users are willing to pay for paid knowledge content, and only 33.8% of users have used paid knowledge content. This shows that consumers' habits of buying knowledge are still in the development stage. Moreover, the question of whether knowledge payment is new or whether users' payment behavior is based on continuous knowledge demand or curiosity remains controversial. The cultivation and use of knowledge payments also depends on the cultivation of user habits, i.e., how to move from curiosity to the habit of knowledge seeking.

Furthermore, the value of knowledge-based products depends on online knowledge payment platforms acting as service brokers, creating multiple products through partnerships with knowledge providers, and ensuring that the quality of the knowledge product matches customer preferences [9]. However, due to the information asymmetry in this context, it is difficult for knowledge seekers to know the actual quality of knowledge products before making a purchase decision. With the continuous influx of knowledge providers into the knowledge payment market, the degree of homogenization of knowledge payment products has gradually manifested itself, leading to an intensified competitive situation and an increasingly challenging knowledge payment market. Therefore, it is important for knowledge providers and platform developers to understand the information adoption mechanisms for different types of knowledge products on online knowledge payment platforms. In particular, understanding the factors driving online knowledge payment behavior is critical for knowledge providers to compete for knowledge seekers, achieve financial gains and sustainability, and improve their interactions with knowledge seekers [10–12].

The extant literature on knowledge payment mechanisms and behaviors has examined various factors related to the characteristics of knowledge demanders and providers, knowledge products and services, and knowledge payment platforms [3,7,13]. However, three important research gaps remain in the existing literature. First, although product description is an important part of the product development process and influences users' payment decisions, there is limited evidence on how the information quality of product description influences users' payment behavior. Knowledge seekers can access a wealth of information on knowledge platforms and communities. However, research has not yet examined how knowledge seekers process this information and how this process influences knowledge payment behavior. Therefore, it is important to investigate the factors that influence the knowledge payment decision and the moderating variables to gain a more comprehensive understanding of knowledge seekers' payment behavior [3,14]. Second, previous studies have investigated the influence of perceived information quality on knowledge payment willingness [7,13]. Most previous studies, however, focused on perceived information quality, which is a more subjective evaluation of products in the process of using knowledge payment products; little attention has been paid to objective indicators of the information quality of product descriptions. Finally, previous research has examined utilitarian and hedonic consumption in the knowledge payment domain, suggesting that consumers are guided by either hedonic or utilitarian motives and values when choosing knowledge products and services [15,16]. However, the distinction between utilitarian and hedonic values has only been made at the platform level, not at the knowledge payment product level. Akdim, Casaló [17] emphasized the role that hedonic and utilitarian characteristics play in knowledge payment behavior, arguing that hedonic aspects, such as pleasure, motivate consumers to pay for knowledge products and services. Therefore, analyzing the variability of knowledge payment behavior across different product types is warranted.

In view of the above research gaps, this study develops a research model based on the Information Adoption Model (IAM) [18] to analyze the influence of information quality of knowledge product description and credibility of knowledge providers on online knowledge consumers' payment behavior. In the research model, the information quality of knowledge product description was divided into three dimensions, namely: completeness, vividness, and relevance. Knowledge provider credibility was further divided into reputation, experience, and integrity. Product types were divided into utilitarian and hedonic products and examined for their moderating effect on the relationship between information adoption patterns and knowledge payment behavior. To empirically test the proposed model and hypotheses, we collected a sample of 4366 social Q&A product data from Quora+ (https://www.quora.com/quoraplus), a leading social Q&A and knowledge payment platform, (accessed on 1 January 2022), from January 2021 to January 2022. We examined the validity of the proposed model and the significance of the relationships between study variables using a mixed methods approach combining text analysis and regression analysis techniques. From a theoretical perspective, this study extends the merits of the information adoption model in the study of knowledge payment behavior and provides an in-depth analysis of the mechanisms underlying online users' online knowledge payment behavior. From a practical perspective, the results of this study can help knowledge payment platforms and knowledge providers promote knowledge-based products more effectively and in a more targeted manner.

The remainder of this paper is organized as follows. Section 2 provides a literature review of the key concepts and theoretical considerations related to knowledge payment platforms and the drivers for their development and adoption. Section 3 discusses the development of the research model and hypotheses. Section 4 describes the research methodology used in the study, including variables, associated measures, and data collection procedures. Section 5 presents the data analysis and results of the study. Section 6 discusses the findings and their implications for research and practice. Section 7 discusses the limitations of this study, followed by an overall conclusion in Section 8.

2. Literature Review

2.1. Online Knowledge Payment

The online knowledge payment platform is, in its broadest sense, a dissemination model in which people share knowledge products and services to generate revenue through online transactions. Knowledge providers create and distribute knowledge products on the platform, while knowledge seekers pay to read, listen to, or watch these products [3]. Online knowledge payment platforms treat knowledge as a commodity, with users paying for customized knowledge and producers benefiting from the exchange of tacit knowledge. In this respect, knowledge payment differs from traditional forms of knowledge exchange and transfer because it has aspects of e-commerce (i.e., buying and selling). From the perspective of e-commerce, online knowledge payment is an online knowledge exchange transaction between knowledge providers and demanders that focuses on the monetary expenditures of online users, i.e., describing and pricing the transactional activity of using their tangible resources to acquire knowledge [3,14].

In addition to parallels with the e-commerce model, online knowledge payments can be characterized based on behavioral science and knowledge management considerations. From a behavioral science perspective, online knowledge payments encompass online users' consumption behavior for knowledge products and services [11,19]. Knowledge transactional behaviors occur in the early stages of consumption, knowledge internalization behaviors occur in the middle stages of consumption, and knowledge diffusion behaviors occur in the late stages of consumption. In the early stages of knowledge consumption, consumers use transactional behaviors to acquire knowledge, related information, skills, and experiences. In the middle stages of knowledge consumption, the consuming subject assimilates the new knowledge and integrates it into his or her cognitive structure. The final phase of knowledge consumption has implications for whether or not knowledge products can be transmitted over the Internet, as well as for the scope and depth of dissemination [13]. This requires knowledge providers to reprocess and update outdated knowledge through knowledge diffusion, which promotes the sprouting of new technologies and new information and increases the stock of knowledge in the consumer network [20,21].

From a knowledge management perspective, knowledge payment platforms represent an emerging ecosystem that brings together all aspects of online knowledge creation, dissemination, service, use, and exploitation [13,22]. With technological advances, online knowledge payment models and platforms such as blogs, online communities, and wikis are becoming ubiquitous contexts for dispersed participants to share knowledge for a variety of different purposes [23–25]. This elevates knowledge payment to the level of a micro-business model. This level is the focus of knowledge payment research, with copyright holders, product interpreters, knowledge leaders, service positioning, distribution channels, technical support, and collaboration networks all involved in the knowledge payment architecture process [24,26,27]. In the development of knowledge payment platforms, four business models have broadly emerged based on how online knowledge seekers acquire knowledge products and services: online subscription model, question-and-answer model, offline interactive mode, and knowledge repository model. Each of these major payment models in the knowledge market has its own advantages and disadvantages, different profit models, content production, and platform deployment [24]. On the other hand, the discrepancy between online knowledge payment behavior and traditional consumption is increasingly becoming distinct. Therefore, several studies have recently focused on the factors influencing online payment behavior and the mechanisms of content acquisition and consumption on online knowledge payment platforms.

2.2. Factors Influencing Knowledge Payment Behavior

In recent years, several studies have been conducted on the factors that influence knowledge payment behavior. Based on the underlying context and ideology of knowledge payment, researchers have examined the factors that influence user behavior from three different perspectives: knowledge providers and demanders, knowledge payment products, and knowledge payment platforms. Table 1 provides an overview of relevant studies.

Table 1. Factors influencing knowledge payment behavior.

Category	Main Factors	Influence Direction	Source
Knowledge payment products	Price	positive	[10,14,19,25]
	Perceived value	Positive	[15,22,28]
Knowledge providers	Quality of service and electronic word-of-mouth	Positive	[16,24,29]
	Reputation, ability and integrity	Positive	[8,30]
	Benevolence	Negative	[1,4,23]
	Perceived quality	Positive	[1,9,31]
Knowledge demanders	Task-driven and subjective norms	Positive	[2,9,32]
	Utilitarian value and hedonic value	Positive	[6,33,34]
	Perceived risk	Negative	[6,13,35]
	Perceived unfairness	Negative	[7]
	Free mentality	Negative	[10,19,26]
Knowledge payment platforms	Convenience	Positive	[11,12]
	Interactivity	Positive	[36,37]
	Accessibility	Positive	[3,11,12]

2.2.1. Knowledge Providers and Demanders

From the perspective of knowledge providers and demanders, studies have examined the impact of demographic factors on willingness to pay, actual payment behavior, and continued payment behavior. Bao and Han [13] found that factors such as gender, age, income, and education of online learners significantly affect willingness to pay. Chen, Liang [38] used perceived value to investigate users' willingness to pay for content and concluded that perceived value and switching barriers influence users' willingness to pay. This perceived value and switching barriers are largely due to the role of perceived utility factors, with product quality and provider reputation only indirectly influencing users' willingness to pay through the perceived utility and benefits of using the content. In an online Q&A community, Lin, et al. [26] reported that students' thirst for knowledge and curiosity are factors that influence their willingness to pay. However, product content and prices are determined by their specific needs (e.g., daily spending restrictions and low price acceptance). In addition, grade level, monthly consumption, and frequency of use influence perceived usefulness, perceived ease of use, and perceived enjoyment of knowledge products [16]. Huo and Li [7] found that information flow among study participants in online consultations follows the common characteristics of searching, questioning, solving, implementing, and sharing, and that demand for health information is the driving factor for knowledge reuse.

2.2.2. Knowledge Payment Products

From the perspective of knowledge payment products, previous research has investigated both positive aspects (e.g., persistence, continuation, and repetition) and negative aspects (e.g., withdrawal, transfer, and churn) to promote online knowledge products that better meet users' needs [19,26,39]. Ling [36] proposed a research framework to understand the mechanism of users' knowledge payment behavior, arguing that knowledge content is the key factor influencing knowledge payment behavior, and context and content jointly influence users' knowledge payment behavior. Using a semi-structured interview method, Liu, Zhao [37] found that the most important factors influencing online users' payment behavior are individual needs, individual perceptions, information quality, subjective norms, convenience, alternatives, and economic factors. Pang, Bao [11] argued that content quality, usefulness, and user recognition are the most important determinants of user demand response. Qi, Ma [12] reported that users make payment decisions based on content creator profile, authentication, content of previous responses, approval number, recognition number, collection number, item number, live number, and title.

In terms of knowledge product adoption, most studies first examined the direct drivers of payment intention and then analyzed the effects of payment intention on actual payment behavior. For example, Shi, Zheng [14] found that payment attitude, subjective norms, and perceived behavioral control significantly and positively affect payment intention. In turn, payment intention and perceived behavioral control significantly and positively affect actual payment behavior, while perceived cost significantly and negatively affects actual payment behavior. Sun, Li [22] conducted a study on users' switching behavior from free to paid online Q&A platforms and found that the cost associated with knowledge products is an important factor influencing users' willingness to switch, and that the cost of uncertainty in selecting paid products and services is due to information asymmetry. Wang and Jiang [29] found that website loyalty, subjective norms, and perceived behavioral control all have a significant and positive influence on the willingness to pay for knowledge, and that perceived behavioral control also has a significant and positive influence on continued payment behavior. Shi, Zheng [14] found that users' willingness to pay for knowledge is significantly and positively influenced by perceived quality of free content, perceived credibility of knowledge producers, and number of perceived participants, and willingness to pay for knowledge in turn significantly and positively influences actual users' payment behavior.

2.2.3. Knowledge Payment Platforms

From the perspective of knowledge payment platforms, previous research has shown that the capabilities of knowledge platforms and communities are an important factor in user satisfaction when analyzing how the platform repeatedly and specifically meets user needs. Zhang, Zhang [4] created a user group profile in which he divided paying users into loyal users, silent users, socioeconomic users, and potential users. Zhang, Zhang [23] found that consumer preferences for the two modes of questioning and watching on online questioning platforms do not differ, but have the characteristics of a typical fan economy, while exploring how the platform can strengthen the ability to provide value-added services. Zhang, Chang [1] has found that communication, interaction, and knowledge sharing are the most important aspects of knowledge utilization. Zhou, et al. [2] emphasize factors such as knowledge leaders (or opinion leaders and moderators) and social interaction as expressions of consideration of user needs (other than knowledge), such as fan psychology and social preferences, and thus advocate expanding the scope of knowledge services. Zhu, et al. [34] found that the service quality of knowledge platforms, the ability to satisfy individual needs, and the provision of continuous value-added experiences have positive effects on alleviating knowledge anxiety and combating knowledge inflation when investigating how the platform improves user experience and satisfaction. Previous research has also examined factors such as varying degrees of personalization [6] and supply and demand uncertainty [37] to determine how they can adjust their pricing strategies and balance platform revenue generation with service value to consumers.

The above research findings indicate that the field of knowledge payments is expanding and attracting a growing number of researchers. Previous research has examined a variety of factors that influence knowledge payment behavior. However, little attention has been paid to the key mechanism of how information quality of product description influences online users' knowledge payment behavior. A wealth of information is available to users on knowledge payment platforms and communities. However, research has not yet examined how knowledge seekers acquire this information and how this aggregation process influences their online payment and purchase behavior for knowledge products. There has also been limited research on the effects of various personality traits of knowledge producers on consumer payment behavior. Moreover, the perceived utility and hedonicity of knowledge payment platforms have only been considered at the knowledge payment platform level. At the knowledge payment product level, the heterogeneity of knowledge payment products and their diverse mechanisms of influence on users' knowledge payment behavior have not been sufficiently explored. Therefore, the aim of this study is to empirically investigate the extent to which the information quality of product description and credibility of knowledge provider influence the knowledge payment behavior of online knowledge seekers, and the moderating role of product type in this context.

3. Theoretical Background and Model Development

3.1. Information Adoption Model

Developed by Sussman and Siegal [18], the information adoption model (IAM) incorporates technologies acceptance model (TAM) [40] concepts along with central and peripheral routes from dual processing theory [41]. The IAM assumes that the perceived usefulness of information is influenced by the quality of the information and the credibility of the information source at different levels of fine-grained processing. Perceived usefulness of information mediates the relationship between information processing and information acquisition. At the high level of processing (peripheral route), information consumers are influenced by simple decision rules, such as the credibility of the information source. On the peripheral route, information consumers do not perform deep cognitive examination of the information content, but infer the quality of the information from the credibility of the source. Information consumers are influenced by detailed analyses of information quality and arguments at a finer level of processing (central path). On the central route, information consumers evaluate the quality of the arguments they use to support their understanding of the information, i.e., when they elaborate, analyze, and summarize the information content [42].

In view of its underlying descriptive and explanatory power, the IAM has been widely used to investigate the factors that influence online users' information adoption behavior in different contexts. For example, Qian, Qianzhou [43] found that the argument quality and source credibility have a positive influence on the perceived usefulness of information to persuade shoppers to use information from travel websites. Yin and Zhang [44] studied the process of information adoption by female consumers when using fashion guide websites and found that information quality and source credibility have a significant influence on information usefulness, which in turn influences information adoption behavior. Daradkeh [45] found that the most important factors influencing information adoption by opinion seekers in online forums are source credibility, relevance, timeliness, accuracy, and comprehensibility. Erkan and Evans [46] developed a medical information adoption model and found that information quality, source credibility, and emotional support have a significant and positive influence on medical information adoption behavior. Li, Zhang [47] adapted the IAM to social media; Changchit, Klaus [48] applied the model to online forums; and Daradkeh [45] examined the value of online reviews using a modified model of the IAM.

Several studies have also extended the application of IAM to the study of the impact of information processing on consumers' payment decisions. For example, Elwalda, Erkan [49] studied the effects of virtual marketing on mobile application users' purchase intention and found that information quality positively influences perceived usefulness and perceived ease of use of the application, information source credibility, and information quantity positively influence perceived usefulness of the application, which in turn positively influences perceived usefulness and perceived ease of use of the application. Cho, et al. [50] found that information quality and information source credibility positively influence perceived usefulness of reviews, which in turn affects information adoption and ultimately travel decision. Erkan and Evans [46] confirmed that information quality, information source credibility, information demand, and users' attitudes toward online reviews indirectly influence purchase intention through information usefulness and information adoption, while users' attitudes toward information directly influence their payment intention.

Based on the above literature, there is ample evidence that both information quality and source credibility reduce the perceived uncertainty of a product, which in turn influences users' payment intentions. Therefore, we aim to extend the theoretical foundations of IAM to online knowledge payment platforms by examining the two main dimensions of IAM—the information quality of product description and knowledge producer credibility—and empirically investigating their influence on knowledge payment behavior in conjunction with the moderating role of product type on this relationship.

3.2. Research Model and Hypotheses

This study, consistent with the IAM, postulates that knowledge seekers should consider both the information quality of product description and credibility of knowledge producer when deciding to pay for knowledge products. The information quality of knowledge product description is measured by three variables: completeness, vividness, and relevance [3,51,52]. The credibility of knowledge producer is measured by three dimensions: reputation, experience, and integrity [7,8,32,45]. In accordance with customers' different purchase motivations and usage experiences, this study classified products into two types, namely utilitarian and hedonic products, where utilitarian products are based on practical utility, while hedonic products are based on entertainment experiences [17,53]. Consistent with previous studies [50,54,55], this study postulates that there are significant differences in the effect paths of product description information quality and knowledge producer credibility on knowledge payment behavior for different product types. Therefore, the moderating effect of product type on the relationship between information quality of product description and credibility of knowledge producer and knowledge payment behavior is also investigated. The research model of this study is shown in Figure 1.

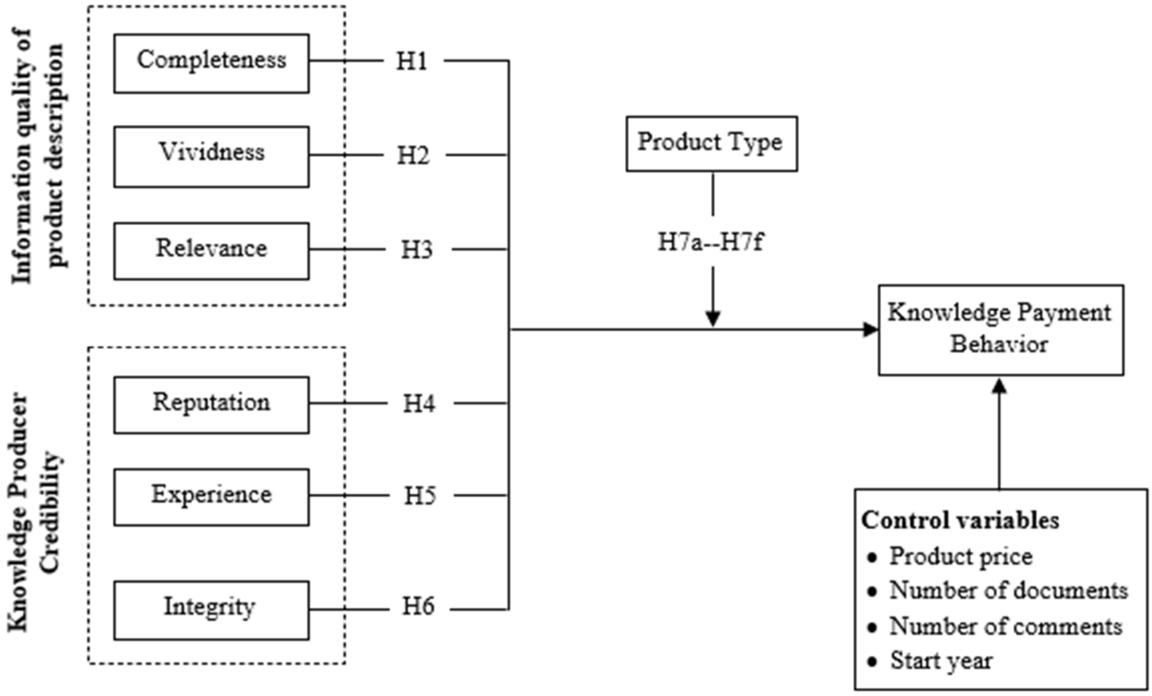

Figure 1. Research model.

3.2.1. Information Quality of Product Description

In this study, the influence of information quality of product description on knowledge payment behavior is investigated based on three dimensions: completeness, vividness, and relevance. Completeness refers to the extent to which a description provides a complete and balanced view of a product or service. Longer textual information and more disclosure of product details promote deeper user knowledge about the product [56], thereby lowering users' perceived risk and encouraging them to make payments [57]. Deng, Xu [58] found that the length of reviews significantly improves users' payment decision behavior. Similarly, Jiang, Liu [57] found that for search products, review length has a significant positive effect on product sales for both popular and unpopular brands. Jiang, Liu [57] used review length to measure product quality and confirmed that user payment behavior increases significantly with review length. Knowledge product description is frequently used by consumers to evaluate product quality. Accordingly, this study hypothesizes that detailed product description will improve consumers' perception of product quality, leading to increased payment behavior. Specifically, the following hypothesis is formulated:

H1. *Product description completeness has a positive impact on knowledge payment behavior.*

Vividness refers to the degree of illustration of the product description. Daradkeh [59] found that both textual description and visual appeal of product images positively influence users' perceived knowledge and mental imagination, which in turn positively affect their willingness to purchase product offerings. Compared to texts, images are more vivid, intuitive, authentic, and attractive to users, reducing their perceived uncertainty and improving their payment behavior. Guo, Wang [60] found that for products with low brand reputation, reviews with images have a significant positive impact on users' purchase decision behavior. Similarly, Akdim, Casaló [17] confirmed that users pay more attention to reviews with pictures when purchasing export products. Daradkeh [59] used the number of images in reviews to measure the quality of online reviews and found that images promote users' purchase decision behavior. By including images in knowledge product descriptions, knowledge providers increase the vividness of the products, promote users' understanding of knowledge products, and help to increase users' payment behavior. Accordingly, the following hypothesis is proposed:

H2. *Product description vividness has a positive impact on knowledge payment behavior.*

The relevance of the product is defined as the extent to which the title and the description of the product are thematically related [57]. In knowledge-based payment platforms, a knowledge product consists of a title and a description, both of which provide the user with detailed information about the product. The product title catches the user's eye and gives a good first impression by providing concise information, while the product description provides comprehensive information about the product features. The mere exposure effect states that a user's attitude toward a stimulus improves when the user is repeatedly exposed to it [13,19,61]. Ardito, Antonio [5] found that users' preference for a review decreases or even disappears if the review title has no relevance to the content of the review, as there is no mere contact effect. Conversely, the higher the relevance of the review title to the content of the review, the higher the users' preference for a review [62]. Therefore, in this study, it is postulated that the higher the relevance of the title of the knowledge payment product to the product description, the more likely it is that users will prefer this knowledge product and stimulate their knowledge payment behavior. Accordingly, the following hypothesis is proposed:

H3. *Product description relevance has a positive impact on knowledge payment behavior.*

3.2.2. Knowledge Producer Credibility

This study posits that knowledge provider credibility, along with product description quality, is an important factor in consumers' evaluation of product quality and influences their payment behavior [32]. In this study, we mainly investigate the three dimensions of knowledge provider credibility: reputation, experience, and integrity, through which knowledge provider payment behavior is influenced.

Reputation is an important factor in building a trust relationship between knowledge providers and knowledge seekers and has a significant impact on users' payment decisions [3,29,30]. Daradkeh [59] found that the number of fans of knowledge providers positively influences users' payment behavior. Tran and Tran [28] also found that the number of followers of audio providers positively influences users' payment behavior. The more followers a knowledge provider has, the more authority and expertise it can demonstrate, which is likely to promote users' payment behavior. Accordingly, the following hypothesis is proposed:

H4. *Knowledge provider reputation has a positive impact on knowledge payment behavior.*

Experience refers to the knowledge and skills that a knowledge producer has acquired through many hours of practice [7]. A higher level of experience makes it more likely that the knowledge producer will be viewed as a reliable source of knowledge, which has implications for user payment behavior [29]. Zhang, Hu [30] showed that the more crowdfunding projects a project sponsor has launched, the more likely the fundraising will be successful. In the context of knowledge payment, knowledge producers acquire specific knowledge and skills by hosting multiple knowledge spaces and live sessions (e.g., Quora Live), which helps to increase the credibility of knowledge producers and thus motivate the payment behavior of knowledge seekers. Zhu, et al. [34] suggested that the number of courses offered by connoisseurs positively influences knowledge product selection and learners' payment behavior. Atulkar [61] found that the number of works by audio distributors helps to stimulate users' payment behavior. Accordingly, the following hypothesis is proposed:

H5. *Knowledge producer experience has a positive impact on knowledge payment behavior.*

Integrity refers to the degree of completeness of the identity information provided by the knowledge provider [32]. The more complete the information provided by the knowledge provider is, the more beneficial it is to improve the provider's credibility, reduce the user's perceived risk, and thus improve the user's purchase decision behavior. Zhu and Zhang [6] found that the trust relationship between tenants and landlords is significantly and positively improved when landlords authenticate themselves with their real names and open a personal homepage on short-term rental platforms. Ha and Kitchen [35] suggested that real name authentication and detailed personal profiles of physicians positively influence users' behavior during paid consultations. Chi, Gursoy [63] found that authenticating knowledge producers with their real names and disclosing their professional field significantly and positively influences users' payment behavior. In the context of knowledge payment, the information disclosed by the knowledge producer includes residence, industry, work experience, and educational experience. This study postulates that the more information a knowledge producer discloses, the higher the knowledge producer's credibility and the more likely users are to pay for the knowledge product. Accordingly, the following hypothesis is formulated:

H6. *Knowledge producer integrity has a positive influence on knowledge payment behavior.*

3.2.3. Moderating Role of Product Type

Knowledge products, while covering a wide range of domains and functions, can be divided into two types: utilitarian and hedonic products [39,54,61,64]. Utilitarian products can satisfy life needs or help in accomplishing tasks, emphasize function and performance, and are based on practical value. Hedonic products, on the other hand, can satisfy intrinsic affective needs, emphasize pleasure and enjoyment, and are based on entertainment experiences [17,39]. Tyrväinen, Karjaluoto [55] argue that users have high involvement when they believe the product is essential. Utilitarian products are necessities that should be purchased, while hedonic products are just non-necessities that they want to buy [38,55]. Utilitarian products are more important than hedonic products. Therefore, users who buy utilitarian products are more likely to be involved than users who buy hedonic products [61].

Previous research has found significant differences in decision behavior between utilitarian and hedonic products. For example, using a meta-analytic approach, Vieira, Santini [64] found that product type significantly moderated the influence of retail marketing channels on customer satisfaction, visit intention, visit behavior, and electronic word of mouth. Similarly, Chi, Gursoy [63] found that product type had a significant moderating effect on the relationship between online review interpretation and the predictability of attitudes and product choice. Shao and Li [53] also found that product type had a significant effect on the relationship between review validity, number of reviews, and review recall and product sales. Wang and Jiang [29] found that users with high involvement pay more attention to persuasive information content such as the quality of reviews. In contrast, low-involvement users rely more on intuitive cues beyond information, such as the number of reviews. Chen, Liang [38] confirmed that the higher the user's involvement, the stronger the influence of review quality on purchase intention. In contrast, the lower the user's involvement, the stronger the impact of the reviewer's status on payment intention.

In the context of knowledge pay products, users who purchase utilitarian knowledge products are in a higher involvement state than users who purchase hedonic knowledge products, leading to differences in the purchase decision process. Vieira, Santini [64] argue that the evaluation process of utilitarian products focuses on cognitively driven product attributes, while the evaluation process of hedonic products places less emphasis on cognitive thought processes. Accordingly, this study postulates that users of utilitarian knowledge products are more likely to prioritize the information quality route. In contrast, users of hedonic knowledge products are more likely to prioritize the information source's credibility. Accordingly, the following hypotheses are posited:

H7a. *Product description completeness of utilitarian products has a stronger positive influence on knowledge payment behavior than that of hedonic products.*

H7b. *Product description vividness of utilitarian products has a stronger positive influence on knowledge payment behavior than that of hedonic products.*

H7c. *Product description relevance of utilitarian products has a stronger positive influence on payment behavior than that of hedonic products.*

H7d. *Knowledge producer reputation of hedonic products has a stronger positive influence on knowledge payment behavior than that of utilitarian products.*

H7e. *The knowledge producer's experience of hedonic products has a stronger positive influence on knowledge payment behavior than that of utilitarian products.*

H7f. *The knowledge producer's integrity of hedonic products has a stronger positive influence on knowledge payment behavior than that of utilitarian products.*

4. Research Methodology

The research models and hypotheses in this study were tested using a standardized analysis procedure, the hierarchical logistic regression model. Based on the logistic function, a hierarchical regression model allows stepwise estimation of probabilities for a binary response variable relative to one or more independent variables [65]. As with any analytic endeavor, data collection, integration, and preprocessing took up a significant portion of the research process. A series of predictive models were then developed (estimation of results and testing of hypotheses) based on the preprocessed, analysis-ready data [45,62]. The results of these models were evaluated and compared using a set of standard measures. Finally, two robustness tests were performed on the data set to validate the estimation results. The research steps, including data sources and collection, variables specification, and model testing, are outlined in this section.

4.1. Data Collection

The dataset used in this study was collected from Quora+ (https://www.quora.com/quoraplus), (accessed on 1 January 2022), a well-known knowledge payment platform and one of the largest social media Q&A platforms that innovatively leverage a virtual knowledge community for knowledge sharing and payment. Quora was launched in 2009 as a social Q&A platform based in Mountain View, California, and has since grown rapidly around the world [66]. Quora connects users with well-known experts and celebrities to whom they can ask questions in exchange for payment. Quora's success has sparked a new global wave of paid Q&A services (Zhihu, DeDao, Weibo QA) [67]. Quora.com receives an average of 3000 to 5000 questions per day from its 300 million monthly users on over 300,000 topics, divided into nine general areas such as medicine, education, and law. Quora focuses on verified real-world experts, distinguishing it from previous paid Q&A services run by an anonymous crowd (e.g., Google Answers). More specifically, Quora uses a targeted model where users ask questions to a specific expert by paying the question fee set by the expert. This model aims to improve expert engagement and motivation. In addition, Quora is the first system that explicitly rewards people for asking good questions. After a question is answered, other community users must pay a subscription of $5 per month or a discounted annual subscription of $50 per year to gain access to the answer. This subscription package is split equally between the questioner and the answerer. A good question can attract enough audience to offset the initial fee for the question.

Quora+ was selected in this study primarily because Quora+ is a new subscription offering from Quora that has already been extensively studied by researchers, and because the insights gained from this study offer deep comparisons and benchmarking implications [3]. Using Quora+, knowledge curators and creators can make independent choices to describe their products and gain credibility, which is a typical environment for evaluating marketing methods for paid knowledge products. Moreover, Quora+ is a typical representative of real-time conversation platforms such as Walnut Live and Zhihu Live. Therefore, the results can be generalized. With the subscription package, users also have unlimited access to exclusive content, answers, and posts. With Quora's new subscription (Quora+), knowledge seekers can communicate with any knowledge providers in various fields and purchase an online knowledge product or service to gain access to the provider's tacit knowledge.

In this study, we used a web crawler developed with Python 3.6 to obtain a total of 5316 Quora Live data from January 2021 to January 2022. This includes information on product sales, product descriptions, prices, number of files, number of reviews, year of launch, domain, number of followers of knowledge producers, number of published Quora Live posts, as well as information on disclosure of residence, industry in which the knowledge producer works, professional experience, and educational experience. We randomly selected services on knowledge topics from eight general areas, including workplace development, industry experience, Internet, psychology, life support, venture finance, education, and investment. After data collection, we excluded samples with missing data and outliers, and finally obtained 3466 items of online knowledge products/services.

4.2. Measurements of Variables

The growth of product sales in knowledge payments generally reflects the payment behavior of users [1,23]. This study therefore uses the growth of product sales (i.e., the number of payment transactions within a given 12-month period) as the dependent variable to ensure objectivity and consistency of the research results.

In terms of information quality of product descriptions, Wang, Mei [16] showed that the text length is the strongest predictor of information quality. Yu, Chen [8] found that text length plays an important role in measuring information quality. The longer the text, the richer the information provided to the user. Therefore, in this study, text length of product description is used to measure the completeness dimension of information quality. Wang and Jiang [29] confirmed that the number of images has a positive impact on the quality of online reviews. Upadhyay, Upadhyay [56] argued that images are more vivid and engaging and can improve users' socio-emotional experience. Therefore, in this study, the number of images is used to measure the vividness dimension of information quality. Zhu, et al. [34] used the text similarity between the text of a given answer and the text of the posed question as an indicator of answer quality. Similarly, in this study, the relevance dimension of information quality is measured by the text similarity index between the product description and the product title.

As for the credibility of knowledge producers, reputation mainly depends on their personal status on the platform, which can be measured by the number of followers on the platform [10,32,37]. Therefore, in this study, the number of followers of knowledge producers is used to measure the reputation dimension of knowledge producers' credibility. Tran and Tran [28] considered the number of online consultations of physicians as an important indicator of their expertise. Canh, Liem [68] suggested that the number of crowdfunding projects founded by a project initiator is an indication of his or her experience. Similarly, in this study, the number of Quora Live posts published by knowledge producers is used to measure the experience dimension of the knowledge producer's credibility. In analyzing the trust relationship between tenants and landlords, Su, Li [15] focused on whether landlords had authenticated themselves with real names and created a personal homepage. Shi, Zheng [14] considered real name authentication and personal profiles as important influencing factors in their study of physicians' paid consultation behavior. Therefore, in this study, the amount of information disclosed by knowledge producers is used to measure the information integrity dimension of knowledge producer credibility.

In line with Basso, Duschitz [39] classification criteria for knowledge payment products, this study classifies knowledge payment products into utilitarian products and hedonic products. Therefore, dummy variables for product type are constructed based on the domain classification. In addition, this study controls for product type, price, number of files, number of reviews, and year of launch. The corresponding description of the variables used in this study are shown in Table 2.

Table 2. Variables description.

Variable Type	Variable Name	Variable Calculation Method	Variable Description
Dependent Variables	Knowledge payment behavior	Statistics	Difference in product sales between January 2021 and January 2022
Independent variables	Completeness	Statistics	Total number of words in the product description
	Vividness	Statistics	Number of images inserted in the product description
	Relevance	Information Extraction	Text similarity between product description and product title calculated using TF-IDF method
	Reputation	Direct access	Number of followers of the knowledge producer
	Experience	Statistics	The number of published Quora Live by the knowledge producer
	Integrity	Statistics	The number of residence, industry, job experience and education experience disclosed by knowledge producers
Moderating variables	Product Type	Classification	Dummy variables: 0 for utilitarian products and 1 for hedonic products
Control variables	Price	Direct Access	Product pricing of Quora Live
	Number of documents	Direct Access	Number of documents uploaded by Quora Live
	Number of comments	Direct Access	Cumulative number of reviews for Zhihu Live in January 2019
	Start Year	Category	Dummy variable, from 2019 to 2022

In this study, the number of Quora live releases and sales indicators in each domain are calculated to understand the distribution of domains (see Table 3). The number of Quora Live publications in each domain varies greatly, with Education having the most publications with 866 publications (18.16%). Food and beverage has the lowest number of publications, with only 12 publications (1.06%). In addition, there are significant differences in the turnover indicators between different domains, with the highest average turnover in psychology and the lowest average turnover in travel, confirming that there are significant differences in the knowledge payment behavior between domains.

Table 3. Descriptive statistical analysis of knowledge domains (topics).

			Sales Volume				
Area	**Frequency**	**Percentage (%)**	**Mean**	**Std. Div.**	**Median**	**Min.**	**Max.**
Education	866	18.16	441.83	783.88	127.00	0	7795
Career	578	12.74	304.34	450.48	120.50	0	7473
Internet	497	11.23	293.29	496.49	103.00	0	7535
Finance & Economy	405	9.51	283.31	477.12	87.00	0	6200
Lifestyle	320	7.91	650.59	3477.38	116.50	0	70,163
Music, Movies and Games	225	6.1	301.06	435.05	102.00	0	4443
Art	131	4.34	261.58	332.37	96.00	0	2886
Science & Technology	147	4.64	461.50	1100.07	112.00	0	8068
Medicine & Health	118	4.1	892.20	1252.50	423.50	0	11,325
Reading and Writing	76	3.31	364.33	601.43	87.00	2	4312
Law	48	2.77	234.28	345.74	67.50	0	1683
Psychology	98	3.71	1161.07	2742.00	243.50	0	16,531
Design	66	3.11	274.67	315.67	112.50	0	2564
Business	22	2.27	218.40	237.52	77.00	0	1475
Sports	50	2.81	632.29	732.05	296.00	0	5615
Travel	27	1.06	124.02	107.73	50.50	0	1201
Food and Beverage	12	2.1	315.42	636.52	73.00	1	4004
Total	4366	100.00	420.45	1252.21	112.00	0	60,163

5. Empirical Results

5.1. Descriptive Statistics

The results of descriptive statistics for the main variables are shown in Table 4. Due to the large variance of the samples of selected variables, which may affect the normality of the data, in this study the continuous variables were treated by a linear transformation using the normal logarithm. In this way, we consolidated the magnitude of the variables, controlled for the potential influence of outliers, and transformed potential nonlinear relationships into linear relationships, making the regression results more robust.

Table 4. Descriptive statistics of study variables.

Variables	Mean	St. Div.	Median	Min.	Max.
Knowledge payment behavior	420.45	1252.21	112.00	0	60,163
Completeness (No. of words in product description)	168.20	88.55	152.50	0	762
Vividness (No. of images)	0.22	0.55	0.00	0	12
Relevance (Text similarity between product description and product title)	0.26	0.22	0.23	0	0.83
Reputation (No. of followers)	53,111	12,011	1144	1	204,921
Experience (No. of Quora Live posts)	6.83	8.69	6.00	1	49
Integrity (Amount of information disclosed)	2.61	3.13	5.00	0	5
Product type	0.19	1.43	1.00	0	1
Product Price	20.09	21.59	17.72	0	500
Number of documents	16.69	22.51	11.00	0	331
Number of comments	142.29	526.40	42.00	0	22,071

5.2. Hypotheses Testing

The results of Pearson correlation coefficient analysis of the main variables are shown in Table 5. Except for vividness, the correlation coefficients between the other independent variables and knowledge payment behavior are significantly positive; therefore, H1 and H3~H6 were tentatively verified. The correlation coefficients between the main independent variables were below 0.5 in most cases, indicating that there was no significant multicollinearity problem, which ensured the reliability of the results for the subsequent multiple regression analysis.

Table 5. Pearson correlation coefficients of key variables.

	1	2	3	4	5	6	7
1. Knowledge payment behavior	1						
2. Completeness	0.1631 *	1					
3. Vividness	0.0003	−0.0312 *	1				
4. Relevance	0.0524 *	0.0635 *	−0.0757 *	1			
5. Reputation	0.380 *	0.0241 *	−0.1254 *	0.0203 *	1		
6. experience	0.1910 *	0.0461 *	−0.0552 *	0.0726 *	0.5313 *	1	
7. Integrity	0.0850 *	0.0317 *	0.0112 *	0.0451 *	0.1753 *	0.1842 *	1

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Because linear regression analysis with cross-sectional data is susceptible to heteroscedasticity, we tested for heteroscedasticity using the White test after running the regression command with Stata/SE 15.1. (StataCorp LLC, TX, USA). It was found that the p-value was significant at the 0.05 level and heteroscedasticity was present. Therefore, the ordinary least squares (OLS) regression method was used. The results of the OLS regression analysis are shown in Table 6.

Table 6. OSL regression analysis results.

Effect Type	Main Variables	Model 1	Model 2	Model 3
Main effect	Completeness		0.071 (2.54) ***	0.046 (1.85) *
	Vividness		0.186 (3.29) ***	0.124 (2.04) **
	Relevance		0.877 (5.64) ***	0.781 (4.39) ***
	Reputation		0.045 (3.40) ***	0.027 (2.39) **
	Experience		0.174 (6.34) ***	0.138 (4.86) ***
	Integrity		0.199 (4.65) ***	0.191 (4.17) ***
Moderating effect	Product type * Completeness			0.057 (1.02)
	Product Type * Vividness			0.212 (1.80) *
	Product type * relevance			0.498 (1.33)
	Product Type * Reputation			0.036 (1.76) *
	Product type * Experience			0.113 (1.70) *
	Product Type * Integrity			0.013 (0.13)
Control effect	Product Type	−0.148 (-2.68) ***	−0.138 (−3.40) ***	−0.158 (−2.71) ***
	Price	0.167 (6.98) ***	0.073 (2.57) ***	0.069 (2.41) **
	Number of documents	0.094 (6.72) ***	0.077 (6.24) ***	0.074 (6.15) ***
	Number of Comments	0.810 (68.30) ***	0.668 (52.29) ***	0.766 (52.31) ***
	Start year	Control	Control	Control
Intercept term	Constant term	0.511 (4.55) ***	−0.171 (−1.15)	0.020 (0.17)
	R2	0.542	0.553	0.554
	F-value	1121.857 ***	613.126 ***	411.547 ***
	N	4366	4366	4366

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

In Model 1, the F-value is 1132.868 ($p < 0.01$) and the regression equation is significant. Model 2 adds independent variables to Model 1, with an F-value of 613.126 ($p < 0.01$). As a result, the regression equation is significant, and all independent variables have a significant and positive influence on knowledge payment behavior; thus, H1~H6 are supported. Specifically, the regression coefficient for product description completeness is 0.071 ($p < 0.01$), product description vividness is 0.186 ($p < 0.01$), and product description relevance is 0.877 ($p < 0.01$), all of which have a positive influence on knowledge payment behavior. These results suggest that increasing the information quality of the product description is more likely to influence users' knowledge payment behavior. The regression coefficient for knowledge provider reputation is 0.045 ($p < 0.01$), experience is 0.174 ($p < 0.01$), and integrity is 0.199 ($p < 0.01$), all of which have a positive influence on knowledge payment behavior. The results suggest that the higher a knowledge producer's reputation and the more experience and information he reveals, the more credible he is and the more willing users are to pay for knowledge products.

In this study, the interaction terms between product type and the corresponding variables were used to test the moderating effect of product type on the relationship between product description information quality and knowledge producer credibility and knowledge payment behavior. The regression results are shown in model 3. The regression coefficient of the interaction term between product type and product description vividness is 0.212 ($p < 0.1$), indicating a stronger influence of hedonic product description vividness compared to utilitarian products, so H7b is rejected. In contrast, the regression coefficient of the interaction term between product type and product description completeness is 0.057 ($p > 0.1$), and the regression coefficient of the interaction term between product type and product description relevance is 0.498 ($p > 0.1$). These results indicate that the effects of completeness and relevance on knowledge payment behavior do not differ significantly between utilitarian and hedonic products, thus H7a and H7c are rejected. The regression coefficient of the interaction term between product type and knowledge producer reputation is 0.036 ($p < 0.1$), and the regression coefficient of the interaction term between product type and knowledge producer experience is 0.113 ($p < 0.1$). These results indicate that the influence of knowledge producer's reputation and experience is stronger for hedonic products than utilitarian products; thus, H7d and H7e are supported. In contrast, the regression coefficient of the interaction term between product type and knowledge producer integrity is 0.013 ($p > 0.1$), indicating that the effect of knowledge producer integrity on knowledge payment behavior is not significantly different for utilitarian and hedonic products; thus, H7f is rejected. Table 7 shows the results of hypotheses testing.

Table 7. Hypotheses testing results.

Dimension	Hypothesis	Remarks
Peripheral route (Information quality of product description)	H1: Product description completeness has a positive impact on users' knowledge payment behavior.	Supported
	H2: Product description vividness has a positive impact on users' knowledge payment behavior.	Supported
	H3: Product description relevance has a positive impact on users' knowledge payment behavior.	Supported
Central route (Knowledge producer credibility)	H4: Knowledge provider reputation has a positive impact on users' knowledge payment behavior.	Supported
	H5: Knowledge producer experience has a positive impact on users' knowledge payment behavior.	Supported
	H6: Knowledge producer's integrity has a positive impact on users' knowledge payment behavior.	Supported
Moderator (Product Type)	H7a: Product description completeness of utilitarian products has a stronger positive impact on knowledge payment behavior than hedonic products.	Not Supported
	H7b: Product description vividness of utilitarian products has a stronger positive impact on knowledge payment behavior than hedonic products.	Not supported
	H7c: Product description relevance of utilitarian products has a stronger positive influence on knowledge payment behavior than hedonic products.	Not supported
	H7d: Knowledge producer reputation of hedonic products has a stronger positive impact on knowledge payment behavior than that of utilitarian products.	Supported
	H7e: Knowledge producer's experience of hedonic products has a stronger positive influence on knowledge payment behavior than that of utilitarian products.	Supported
	H7f: Knowledge producer's integrity of hedonic products has a stronger positive influence on knowledge payment behavior than that of utilitarian products.	Not supported

5.3. Robustness Check

To validate the results, two robustness tests were performed on the dataset. First, since the platform reviewers need to spend some time and effort to evaluate the knowledge products, especially when many products are submitted in a certain period of time, the evaluation of the knowledge product by the platform reviewers may be delayed by 7 days (the reason for choosing 7 days is that the fastest update cycle on Quora Plus is one week). This bias could cause a potential bias in the estimate. Therefore, the model was revalidated by excluding knowledge products submitted less than 7 days before data collection. In addition, when a knowledge provider submits a product, there may be input errors. If the product is submitted before processing is complete, such erroneous submission may bias the estimation results. Therefore, this study re-examines the model by eliminating product content with a description length of less than 15 words to further test the positive relationship between product description completeness and knowledge provider payment behavior. The results in Table 8 show that the results of the two confirmation tests of the new dataset closely match the estimation results of the full dataset; this demonstrates the robustness of the results of this study.

Table 8. Results of Robustness Check.

Independent Variable	(1) Exclude Products Submitted in the Past 6 Months	(2) Exclude Products with Description Length < 15
Completeness	0.057(1.86) *	0.037(1.86) *
Vividness	0.153 (2.05) **	0.133 (2.05) **
Relevance	0.770 (4.39) ***	0.750 (4.39) ***
Reputation	0.016 (2.49) **	0.016 (2.49) **
Experience	0.149 (4.96) ***	0.129 (4.96) ***
Integrity	0.180 (4.18) ***	0.160 (4.18) ***
Product type * Completeness	0.046 (1.01)	0.036 (1.01)
Product Type * Vividness	0.221 (1.90) *	0.201 (1.90) *
Product type * relevance	0.447 (1.34)	0.437 (1.34)
Product Type * Reputation	0.031 (1.77) *	0.027 (1.77) *
Product type * Experience	0.113 (1.80) *	0.011 (1.80) *
Product Type * Integrity	0.013 (0.12)	0.031 (0.12)
Product Type	−0.146 (−2.91) ***	−0.135 (−2.91) ***
Price	0.058 (2.42) **	0.047 (2.42) **
Number of documents	0.064 (6.16) ***	0.062 (6.16) ***
Number of comments	0.603 (62.33) ***	0.633 (62.33) ***
Start year	Control	Control
Constant term	0.033 (0.18)	0.045 (0.18)
R2	0.302	0.422
F-value	447.533 ***	366.504 ***
N	416	426

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

6. Research Findings and Implications

6.1. Research Findings

Based on the information adoption model, this study developed a research model to investigate the influence of the information quality of product description and credibility of knowledge provider on users' knowledge payment behavior, and examine the moderating effect of product type on this relationship. The results show that the completeness, vividness, and relevance of the product description and the reputation, experience, and integrity of the knowledge provider positively influence knowledge payment behavior. In addition, product type significantly and positively moderates the relationship between knowledge provider reputation and experience and knowledge payment behavior.

Compared to utilitarian products, the vividness of hedonic products has a more pronounced positive influence on knowledge payment behavior. One possible explanation for this finding is that hedonic products focus more on the emotional experience that the product brings than utilitarian products, and that pictures can better illustrate ideas that are difficult to express in words and help enhance users' socio-emotional experience. However, the relationships between product description completeness and relevance and knowledge payment behavior, as well as the relationship between knowledge provider information integrity and knowledge payment behavior, did not show significant differences between utilitarian and hedonic products. This suggests that for different product types, the degree of completeness of information, the degree of relevance of content, and the degree of information integrity of the knowledge provider are equally important for the knowledge payment decision, and that there are no divergent effects due to different degrees of engagement.

6.2. Theoretical Implications

The findings of this study have several theoretical implications for the current relevant literature. First, this study contributes to the current stream of research that has recently emerged to examine the factors that influence knowledge payment behavior. Knowledge consumers have a wealth of options for finding information on knowledge payment platforms, but research has not yet examined how knowledge demanders assimilate this knowledge and how this assimilation process influences payment behavior. By expanding the applicability of the information adoption model in the context of knowledge payment platforms, this study provides a deeper understanding of the factors that influence users' payment decisions on knowledge payment platforms and introduces valuable moderating variables for a more comprehensive and broader analysis.

Second, this study examined the moderating role of product type in the relationships between product description information quality and knowledge provider credibility and knowledge payment behavior. Although the literature has examined the effects of perceived utility and perceived hedonic value of knowledge payment platforms on user satisfaction, the distinction between utility and hedonic value has not yet been applied to the knowledge payment product level. By distinguishing different types of knowledge payment products, this study found that users pay different attention to each influencing factor when purchasing utilitarian and hedonic products. This finding not only enriches the research literature on knowledge payment behavior, but also provides a solid theoretical foundation for knowledge payment product design and marketing practice. The diversification of knowledge payment products and services supports the diversification of payment models in the knowledge payment industry. The results of this study suggest that the different types of knowledge products meet the psychological needs of knowledge consumers, stimulate knowledge consumers' willingness to pay for knowledge, and are conducive to the development of the knowledge payment industry.

Finally, this study provides a thorough understanding of how to develop an effective combination of online marketing strategies for knowledge producers and knowledge payment platforms. The results of this study highlight the differences in action paths between different product types and provide useful guidelines for knowledge producers and knowledge payment platforms to target and manage product descriptions and their own information. These results suggest that as the ability of paid knowledge users to identify and filter knowledge products improves, the immersion and improvement of experience demand and the expansion and broadening of experience demand lead paid knowledge users to repurchase products, and that the repurchase rate of knowledge payment platforms has indeed become key to influencing revenue. The repurchase rate of knowledge-based products can be divided into horizontal repurchase rate and vertical repurchase rate. The joint expansion of vertical and horizontal repurchases is the key to the sustainable development of knowledge payment behavior.

6.3. Practical Implications

The findings of this study also have several implications for knowledge providers, consumers, pay-for-knowledge platform operators, and policymakers in the digital knowledge economy. First, the results of this study suggest that knowledge providers should describe basic product information in as much detail as possible to encourage user payment behavior to reduce information asymmetries. Similarly, product descriptions should be supplemented with images to vividly convey product information to users. To avoid unnecessary information and ensure content relevance, knowledge products/services should be described in a relevant way to accurately convey the information of paid knowledge products. Knowledge producers can also improve their reputation by answering questions for free and actively posting related content whenever possible, improve their experience by participating in Quora Live multiple times, and improve their integrity by improving their profile information. Compared with utilitarian products, the descriptions of hedonic products should be mainly supplemented by pictures. However, compared to utilitarian products, knowledge producers of hedonic products should pay special attention to improving their reputation and experience.

Second, the results of this study suggest that knowledge platform operators should encourage knowledge producers to use images to support product information description and require knowledge producers to focus on product topics when describing product information. In this context, an automated system can be developed to calculate the text similarity between product titles and product descriptions in real time using text mining tools and provide knowledge producers with visual and objective indicators to improve product description. To augment and improve product description, images should be emphasized in the description rules for hedonic products as opposed to utilitarian products. Compared with utilitarian products, it is especially important to expand the channels to improve the reputation of knowledge producers of hedonic products and encourage knowledge producers to continuously produce paid knowledge products.

Third, the results of this study suggest that knowledge payment platforms can maximize the stimulation of users' knowledge payment behavior through the synergy of two types of information, namely product descriptions and personal characteristics. By understanding the key influencing factors of users' knowledge payment behavior, knowledge payment platforms can develop and design better decision support systems for users. Considering that the information quality of product descriptions and the credibility characteristics of knowledge producers have a significant and positive influence on users' payment behaviors, a set of indicators of product descriptions and knowledge producers' characteristics can be integrated into the display panels of knowledge payment products to create a more comprehensive product selection mechanism, improve the efficiency of users' information selection, and effectively reduce users' cognitive processing load. Considering the different effects of product descriptions and characteristics of knowledge producers on payment behaviors for utilitarian and hedonic products, it is necessary to add a classification function for product types.

Finally, the results of this study suggest that accurate prediction of users' payment behaviors is crucial for knowledge payment platforms' product marketing and R&D strategies. Knowledge payment platforms can predict the marketing situation of knowledge payment products through the information quality and credibility characteristics of knowledge producers, so as to appropriately adjust the advertising focus and reasonably allocate resources, and ultimately improve the overall dynamics of knowledge payment platforms to ensure the prosperity and sustainable development of the platforms.

7. Limitation and Future Studies

Notwithstanding the implications for research and practice discussed above, this study has a number of limitations that should be considered when interpreting the results. First, the data in this study are cross-sectional. Because knowledge producer information changes dynamically, it is suggested that panel data be collected in subsequent studies to better examine the dynamic effect of information source credibility on user payment behavior. The number of users paying for knowledge has increased rapidly worldwide, and the market for knowledge payments will accelerate with the application of AI, 5G, IOT, and other cutting-edge technologies. Therefore, a promising research direction could be to study factors affecting payment behavior based on a multivariate analysis method. Payment behavior research is particularly focused on realistic and practical aspects, which means that the researcher should be as close as possible to the person under study to ensure that the research process is properly completed.

Second, only one knowledge payment business model was studied (Quora+), and the question remains whether the results are transferable to other knowledge payment business models. Issues such as user perceptions, information behavior, and innovation performance of knowledge payment platforms are influenced not only by the knowledge itself, e.g., content quality, utility, and legitimacy, but more importantly by external contextual factors such as social interaction, opinion leadership, group norms, and ownership protection. Indeed, there are many contributing variables, and user decision-making processes often rely on a combination of factors. Therefore, field research, group analysis, experimental research, and case studies can be used to analyze the influencing factors of knowledge payments in depth, explore the value of knowledge, cultivate users' online payment habits, improve the service quality of knowledge payment products, and promote the dissemination of the new knowledge payment industry.

Third, the variability of factors affecting users' payment behavior in different cultural contexts is not compared. Future research can therefore compare and analyze the different effects of information quality and credibility of knowledge producers on payment behavior for knowledge payment products in different countries.

8. Conclusions

With the proliferation of online knowledge payment platforms, the acquisition of knowledge through purchase has become increasingly common. However, there is limited research on the key factors that influence users' payment behavior. This study investigates the influence of information quality of product descriptions and credibility of knowledge producers on users' payment behavior, and examines the moderating effect of product types. In addition, this study classifies knowledge payment products into utilitarian and hedonic products and compares the differences in action paths between different product types. The results show that completeness, vividness, and relevance of product descriptions have a significant positive effect on knowledge payment behavior. Similarly, reputation, experience, and information integrity of knowledge producers have a significant positive effect on knowledge payment behavior. Compared to utilitarian knowledge products, the reputation and experience of knowledge producers have a greater effect on knowledge payment behavior for hedonic products.

The results of this study extend the applicability of the information adoption model in the context of knowledge payment models and provide a practical blueprint for the design and marketing of knowledge payment products. As paying knowledge users improve their ability to identify and filter knowledge products, the demand for deeper and extended experiences drives paying knowledge users to repurchase knowledge products. Understanding the relevant factors of knowledge payment platforms can help in developing an effective organizational plan and improvement strategy to enhance knowledge providers' capabilities and achieve a price premium for their services, rapid implementation, and targeted marketing.

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